2021 12th International Conference on Information and Communication Systems (ICICS) | 978-1-6654-3351-8/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICICS52457.2021.9464596

Arabic Handwritten Characters Recognition Using Convolutional Neural Network

Mohammed N AlJarrah, Mo'ath M Zyout, Rehab Duwairi
mnaljarrah18@cit.just.edu.jo, mmzyout18@cit.just.edu.jo, rehab@just.edu.jo
Department of Computer Information Systems
Jordan University of Science and Technology
Irbid, Jordan

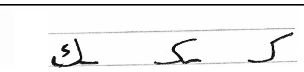
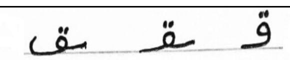
***Abstract*—Automatic handwritten characters' recognition is one of Artificial intelligence applications which is considered an interesting research area and important in various fields. Many studies have been conducted for the recognition of English handwritten characters and fewer works are available for the Arabic language because of the diversity in characters' shapes according to their positions in the words. Convolutional Neural Networks are efficient for handwritten characters' recognition. In this paper, a Convolutional Neural Network has been proposed for handwritten characters' recognition. The model has been trained on a dataset of 16,800 images of handwritten Arabic characters with different shapes to perform classification. The proposed model achieved high recognition accuracy of 97.2%, outperforming other state-of-art models. When applying data augmentation, the model achieved better results and accuracy of 97.7%**

Keywords—Convolutional Neural Network, Deep Learning, Arabic Handwritten Recognition.

I. INTRODUCTION

Deep learning is a subtopic of machine learning, which in turn is also a subtopic of artificial intelligence [1]. One of its definitions is that it uses multiple layers to progressively extract higher-level features from the raw input [2]. It may be distinguished from machine learning by the ease of feature engineering. In machine learning, it is a process that depends on human action while in deep learning it is automatic to some extent through the deep learning model. Deep learning has several different architectures such as Deep Neural Network, Deep Belief Network, Recurrent Neural Network, and Convolution Neural Network (CNN), with these architectures, deep learning proved to be a tremendous success in many applications such as computer vision, machine vision, speech recognition, natural language processing, and audio recognition [2][3]. This paper depends wholly on CNN which is a deep neural network class that is most used to analyze visual imagery [4]. Also, is has applications in image and video recognition, recommender systems, image classification, and medical image analysis [5]. CNN uses and applications are not limited to images only, it may also be used with natural language processing [6]. The benefit of using a convolution layer may be that it reduces the size of the input image while at the same time preserving the spatial properties. In another word, if we are inserted a picture of a human face, it will reduce its size by keeping the shape of the eyes, nose, and mouth. However, this paper will rely on CNN by inserting handwritten characters as images. Handwritten characters' recognition is the ability of the system to recognize and identify the characters that are handwritten in different languages. Arabic "العربية" is one of the Semitic languages that consists of 28 alphabet characters and the mother language of millions of people in about 26 countries worldwide, also for the Islamic people is a language of Holy Qur'an "القران الكريم" [7]. The recognition of Arabic handwritten characters is a complex task and is considered a research challenge; because of the variation in styles of characters where each Arabic character is written in different forms depending on its position in a word: beginning, middle, or end [8]. Table 1 illustrates some Arabic characters in different shapes. Also, one of the issues that may form a challenge in building a system to recognize Arabic handwritten characters is the scarcity of required data and the difficulty in finding a suitable and public dataset for Arabic handwritten characters [9].

Table. 1. Sample of Arabic characters and its variations

Arabic Character	*Different Shapes*
ك	
ق	
ب	
ص	

Many studies have been conducted to recognize various Latin handwritten characters using a CNN that works efficiently and perform well with the recognition process. Since there are fewer studies for the recognition of Arabic handwritten characters, this study provides a CNN model for Arabic handwritten characters recognition.

The rest of the paper is organized as follows: Section 2 provides a review of some related work conducted in the field. Section 3 describes the Arabic dataset used. Section 4 illustrates the structure of the proposed CNN. Section 5 describes the methodology of the proposed approach, discussing the data preprocessing, feature extraction, fully connected layers, and how to train and evaluate the model. Section 6 discusses the experiments and results. Finally, section 7 presents and lists a conclusion of the study.

II. Related work

Since many studies that have been proposed are discussed the various handwriting recognition system for Latin languages, Najwa et al. [10], decide to research this field by performing a study to employ the Arabic language in the recognition systems by creating and collecting a dataset which represents Arabic Hijja letters. The study leverage from Hijja dataset that contains about 47,434 characters and other Arabic Handwritten character to be trained by deep learning model with CNN to perform handwriting recognition. The architecture of the proposed CNN model consists of the convolutional layer which is a number of kernels to detect the features and to introduce a set of feature maps to be passed for the next layer, and pooling layer that reduces the dimension of each feature map, finally, fully connected layer to make the prediction. As findings of the study, the proposed CNN model achieves high accuracy, thus training the recognition model on the Arabic language outperforms other models that applied to Latin languages.

As the characters handwritten recognition gained importance, the recognition of handwritten numeral is an area of research. Ghazanfar et al. [11], provide a CNN based deep learning model for the recognition of handwritten numerals by various languages: Eastern Arabic, Western Arabic, Devanagari, Urdu, and Persian. The proposed model receives the input as an image then performs convolution operation by apply filters with 5*5 size and max-pooling with 2*2 filter size. As the results of the model when trained on all languages together achieves high accuracy with 99.26%, while it is achieving more accuracy when trained on each language individually with a percent of 99.322%.

The recognition of Arabic handwritten language is considered difficult to implement by traditional techniques, so most researchers leverage from deep learning as a valid tool to accomplish Arabic recognition. Khaled et al. [12], provide a deep learning model that employs CNN for the recognition of Arabic handwritten characters. AIA9k [13] and AHCD are two datasets that were used to train the proposed model with three convolutional layers and a fully connected layer. The CNN model applies batch normalization to perform well and avoid overfitting, thus achieving high accuracy for two datasets with 94.8% and 97.6%, respectively.

The study in [14], provides a deep neural network for Arabic handwritten alphanumeric character recognition called VGG net similar to the VGGNet neural network [15] with some improvements. The proposed network was trained on two datasets: HACDB [16] and ADBase [17] databases with architecture consist of 13 convolutional layers to capture features, 2 max-pooling layers to reduce the dimensions and the size of the image, and 3 fully connected layers to produce a prediction. To gain good accuracy and prevent overfitting, the network performs data augmentation and dropout which are two regularization techniques. The results of the study show that the proposed network achieved high accuracy of 99.66% for the ADBase database and 97.32% for the HACDB database.

In most researches, deep learning algorithms have been worked efficiently and perform well with Arabic recognition. El-Sawy et al. [18], propose a CNN to implement the recognition of Arabic handwritten characters by training the model on 16800 handwritten Arabic characters. The proposed model was constructed of 2 convolutional layers to extract features from the input that are images or sound, pooling layers, and fully connected layers that connect all neurons in the previous layer with every neuron it has. Also, the model applies regularization and optimization techniques to get better

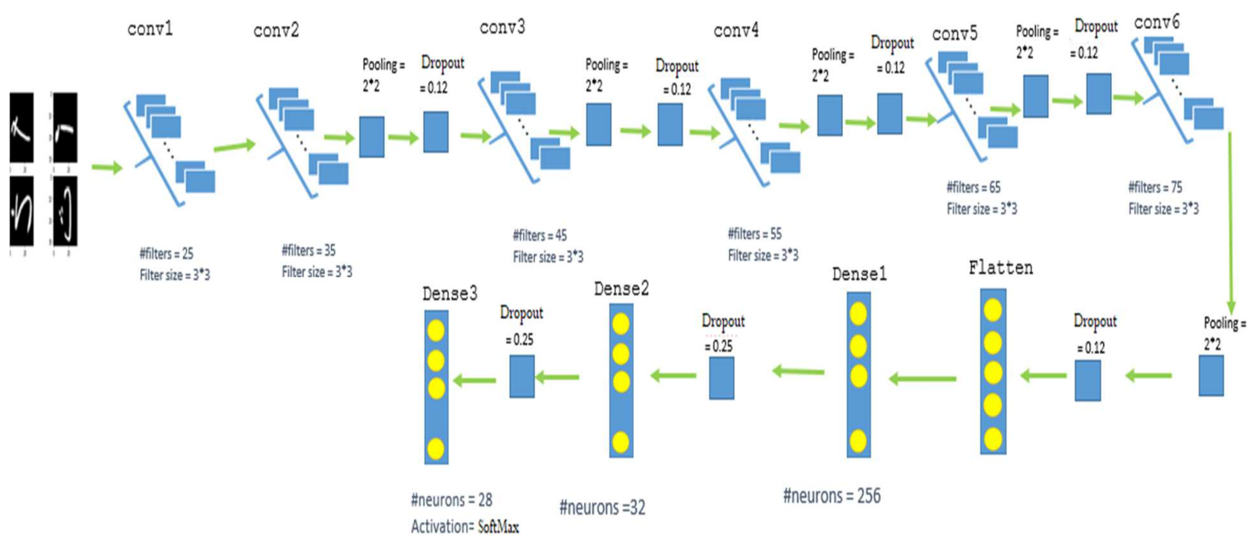


Fig. 1. The Proposed CNN Model for Arabic Handwritten Recognition

performance and accuracy. When the testing process is performed, the model achieves good accuracy of about 94.9%, thus low misclassification error.

Recently, handwritten recognition systems have been developed for various languages based on the available algorithms that make the task smoother. Md. Mahbubar et al. [19], provide a deep learning model that uses CNN to perform the recognition system for the Bangla handwritten characters. The model was trained on 2000 handwritten characters with 400 different samples for each character, using two convolution layers with 5*5 filter size and two pooling layers without extracting the features. The results of the proposed model gained good accuracy of 85.96 % and performed well in the recognition of Bangla handwritten characters.

Behnam et al. [20] also research the effectiveness of CNN in the recognition of Persian handwritten characters by executing two methods of CNN: Single and Ensemble CNN to be trained on Persian handwritten characters. As findings of the experiment, the single CNN achieves good accuracy of 96.3% in the recognition of different shapes and styles of Persian handwritten characters. Furthermore, the CNN has shown noticeable improvement in handwritten characters recognition where in the study [21], Mujtaba et al. generate a dataset of Urdu handwritten characters to perform experiments of the recognition of Urdu handwritten characters by implementing the architecture of CNN.

MK Elbashir et al. [22], build a CNN model to recognize Arabic handwritten characters using a dataset from Sudan University of Science and Technology - Arabic Language Technology Group called SUST ALT. The proposed model is constructed of INPUT layer, CONV layers, POOL layers, and fully connected layers. RELU activation function was used in the model. The image preprocessing has been performed before training, where the size of the image changes and moves the character into the center of the image. The results show that the proposed model achieved an accuracy rate of 93.5 for training while 97.5 for testing.

The study in [23], provides a CNN architecture that includes SVM as a recognizer to make predictions separated by dropout layers to avoid overfitting. HACDB and IFN/ENIT [24] are two datasets that have been used for training and testing. The usage of the CNN model and SVM as a recognizer minimizes the error rate for the HACDB dataset from 6.59% to 5.83% with 66 classes. In comparison, it minimizes the error rate from 7.32% to 7.05% for the IFN/ENIT dataset.

Sulaiman et al. [25], propose an OCR approach for isolated offline Pashto characters recognition and provide a medium-sized database containing 4488 samples of handwritten Pashto characters. The proposed OCR approach has been performed using Convolution Neural Network (CNN) which achieved an accuracy rate of 80.7% outperforming other traditional models.

In [26], Mohamed et al. build a Deep Belief Neural Network (DBN) for Arabic handwritten character recognition using two databases that rely on two levels. The DBN model is constructed of a set of hidden layers. As the study results, the word-level ADAB dataset doesn't achieve good results while for the character level HACDB database the error rate is 2.1%.

In the research in [27], two models: MLP and CNN, have been proposed for Arabic numerals recognition. CMATERDB 3.3.1 database [28] was used, which includes an Arabic handwritten numerals and contains about 3000 images; each image has a size of 1024 pixels. MLP model contains four hidden layers, separated by dropout layers. The CNN model is constructed of two-dimension convolutional layers, dropout layers, and fully connected layers to make predictions. For training, the CNN model needs to reshape the image from one-dimension 1024 pixels into two dimensions 32*32 pixels. As the findings of the research, the CNN model achieved an accuracy rate of 97.4%, outperforming the MLP model that achieved an accuracy of 93.8%.

In this work, the proposed model is different from the mentioned related works in its architecture, where odd filter numbers and standard values for dropout layers in two stages (feature extraction and prediction) were adopted. Also, the size of images has not been resized.

III. DATASET

This study uses a dataset of Arabic handwritten characters called AHCD provided by El-Sawy et al. [18]; it consists of 16,800 Arabic characters written by 60 participants ranging in age between 19 to 40 years and most of the participants are right-hand. Each participant represents each character 10 times in two forms (from "أ" to "ي"). The used dataset is divided into training and testing. The training set is composed of 13,440 characters while the rest 3,360 characters are the testing set. Figure2 shows a sample of the Arabic handwritten characters dataset.

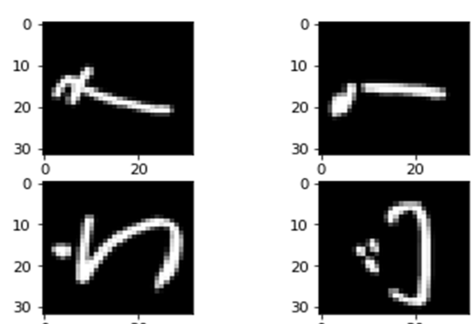


Fig. 2. Arabic handwritten characters dataset

IV. CONVOLUTIONAL NEURAL NETWORK (CNN)

In this study, a CNN model for Arabic handwritten recognition has been proposed. It is constructed by six convolution layers with different functions to predict and recognize images of 32*32 shape size. Three fully connected layers in the model perform characters' recognition. Figure 3 illustrates the architecture of the proposed approach. The CNN model starting with the first convolution layer with 25 filters and 3*3 kernel size, then the rest 5 convolution layers followed by max-pooling layers with 2*2 filter size and dropout layers with 0.12. Finally, three fully connected layers (Dense layers) with SoftMax activation function to perform prediction. Moreover, several filters have been applied for each convolution layer where 25 filters for the first convolution, 35 filters for the second convolution, 45 filters for the third convolution, 55 filters for fourth convolution, 65 filters for fifth convolution, and 75 filters for the Sixth convolution, which secured better performance of the model. Relu, nonlinear activation function, was used to remove negative values by converting them into zeros. The values of weights and bias are updated by a backward propagation process to minimize the loss function.

V. METHODOLOGY

This section presents the methodology of the proposed approach in this study, which consists of four stages.

1. *Data Preprocessing*

The dataset has been read in the form of array as one vector for each character. Each image needs to be transformed from 1024 pixel vectors into 32*32 pixel grid, then convert RGB image to grayscale image.

2. *Feature Extraction*

Low-level features are extracted in the first convolution layer by performing the conventional operation that depends on the number of filters and each filter size. Each image in the dataset has 32*32 size with 1024 pixels, thus a spatial feature for each region in the image has been extracted to recognize each character. Firstly, applying 25 filters to capture regions, then increasing the number of filters up to 35 to find more specified regions in the image in the second layer. This pattern will be repeated until the Flatten layer that transforms each feature map into one-dimension vector to be as input for the fully connected layer. Figure 3.A illustrates the conventional operation for feature extraction with respect to applying the Relu function.

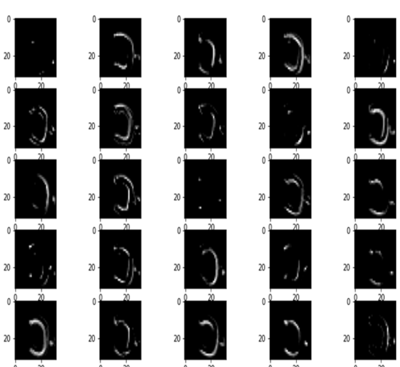


Fig. 3.A. Convolution Layer1

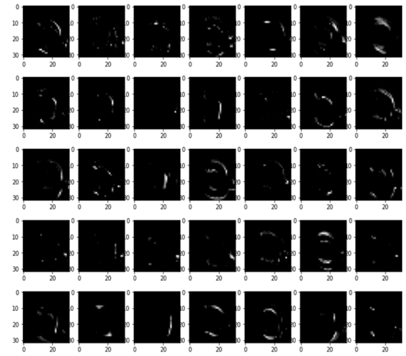


Fig. 3.B. Convolution Layer2

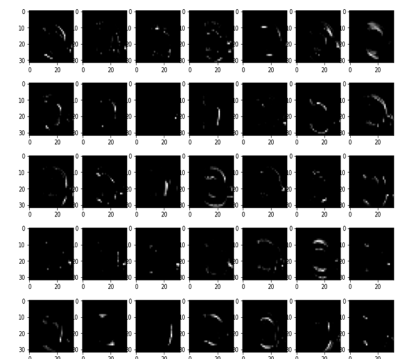


Fig. 3.C. Convolution Layer3

Fig. 3.D. Convolution Layer6

After convolution, downsampling with 2*2 filter size has been applied for each feature map. Moreover, dropout with 0.12 between convolution layers and 0.25 between fully connected layers is performed to deactivate some neurons to avoid overfitting.

3. *Fully Connected Layers*

In this study, the proposed CNN model consists of three fully connected layers. The first dense layer has 256 neurons, the second one has 64 neurons, and 28 neurons for the last dense layer which represents the outputs of prediction. Relu function has been applied for the first two dense layers while SoftMax function was used for the last dense layer which transforms the outputs into probability distribution and provides values between 0 and 1. The output values as a vector represent the probability of each image with 28 character classes.

4. Training and Evaluation of the CNN Model

The proposed CNN model leverages from Keras API to perform training by setting some hyperparameters such as Adam optimizer, learning rate with a value of 0.001, and L2 regularization with a standard value of 0.01. Furthermore, 40 batch size and perform 50 epochs for training. At the last 10 epochs of the experiment, it was monitored that the model achieving training accuracy between 96 and 97, and testing accuracy between 96 and 97.2 with different batches.

VI. RESULTS

While training the model on 40 batch size, the model has performed well. Figure 4 illustrates the accuracy and loss function for both training and testing sets with 40 batch size. At specific epochs, the training and testing accuracy decreased or increased with a value of 1% while the Cross-entropy loss function has been optimized, thus the model achieved good performance to update the weights and bias to perform the recognition.

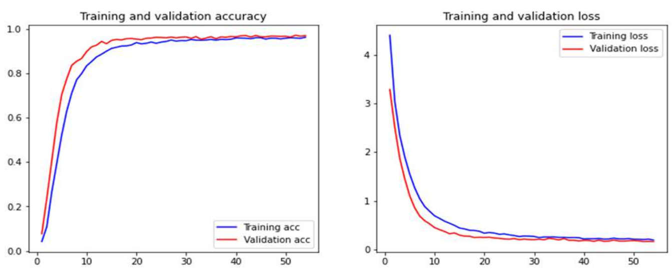


Fig. 4. The accuracy and loss function with 40 batch size

To improve the accuracy, the batch size has been increased to 256, therefore achieve better accuracy of more than 97%. Figure 5 illustrates the accuracy and loss function for both training and testing sets with 256 batch size.

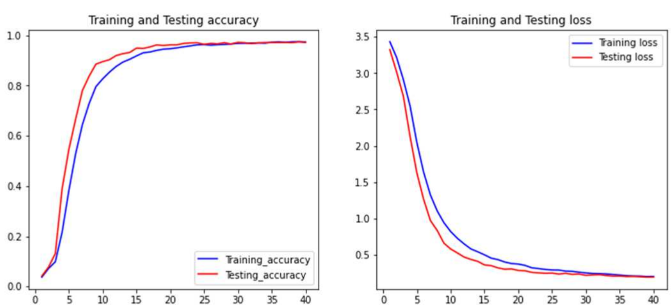


Fig. 5. The accuracy and loss function with 256 batch size

To describe the performance of the proposed model, a confusion matrix has been calculated on a set of test data. Each number represents a special character in the dataset such as “zero” represents “أ” and “1” represents “ب”. The testing dataset contains 3360 images for different Arabic characters, where each character has 120 images. according to the confusion matrix, it was observed that the model was able recognize all 120 images for the “أ” and “ب” characters with 100% accuracy, while the model was able to recognize 112 images out of 120 for the “ث” character with 93%. Figure 6 shows the confusion matrix of the proposed CNN model.

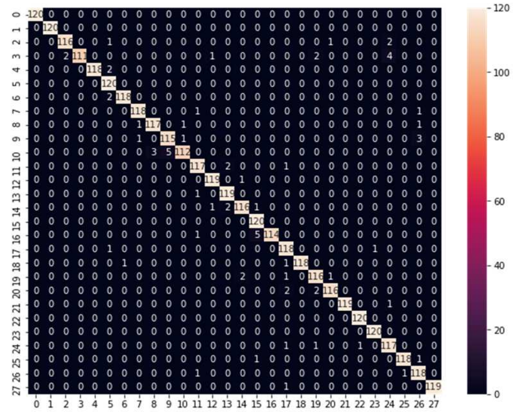


Fig. 6. The Confusion Matrix of CNN model

- *Data Augmentation*

Data augmentation is a set of techniques used to increase the amount of training dataset by applying some transformations to reduce high variance and build better models [29]. Various recognition tasks using deep learning algorithms require a large amount of data for training to be successfully executed, due to the scarcity of data, some recognition tasks do not perform well, so the data augmentation techniques are considered as an effective data-space solution to overcome this challenge and achieve better results [30]. In this work, despite majestic results that were achieved, data augmentation techniques have been applied to improve model performance and attain better recognition results. The following Figure 7 (A and B) illustrates the accuracy and loss function for both training and testing sets with applying data augmentation when batch size is 40 and 256.

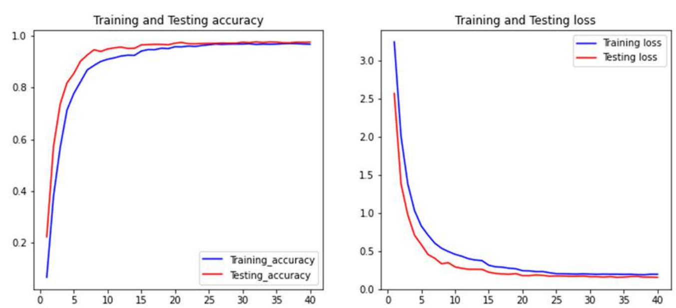


Fig. 7.A. The accuracy and loss function with data augmentation and 40 batch size

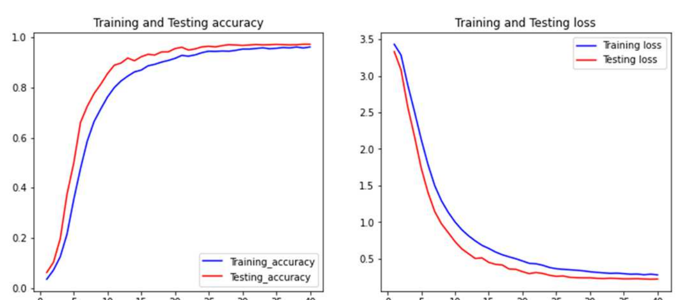


Fig. 7.B. The accuracy and loss function with data augmentation and 256 batch size

when data augmentation has been applied, the performance of the model did not improve notably. The accuracy rate while training the model on 40 batch size is 97.7%, while 97.3% when 256 batch size.

- *Comparison*

This section presents a comparison between our approach and other related studies conducted on the same and different datasets as illustrated in Table 2.

Table. 2. Summary of performance of related approaches compared with our approach

Reference	*Year*	*Dataset*	*Size/Characters*	*Accuracy Results*
[18]	2017	AHCD	16.800	94.9%
[31]	2017	AHCD	16.800	99.8%
[10]	2017	AIA9K	8737	94.8%
[12]	2018	AHCD	16.800	97.6%
Our Approach	2021	AHCD	16.800	97.2%
Our Approach with Data Augmentation	2021	AHCD	16.800	97.7%

According to the comparisons, the results of this work on the AHCD dataset are outstanding compared with other studies and outperforming those introduced in [18], in which the dataset was released and collected. Furthermore, the using of CNN from scratch to recognize the Arabic handwritten characters performed well than using pre-trained CNNs, this what proved in this work as well as in [31].

VII. CONCLUSION

Since there is few research about the recognition of Arabic handwritten characters, this study proposed a CNN model for Arabic Handwritten Characters' Recognition. The model has been trained on a large images dataset called AHCD which contains about 16,800 Arabic handwritten characters in different styles and variances. The results of the work showed outstanding recognition performance on the testing dataset compared with other models - where the proposed model achieved accuracy equals to 97.2%. Data augmentation has been applied to improve the performance of the model where accuracy has improved and equal to 97.7%

REFERENCES

[1] K. G. Kim, "Deep learning book review," *Nature*, vol. 29, no. 7553, pp. 1–73, 2019.

[2] J. Schmidhuber, "Deep Learning in neural networks: An overview," *Neural Networks*, vol. 61. Elsevier Ltd, pp. 85–117, 01-Jan-2015, doi: 10.1016/j.neunet.2014.09.003.

[3] L. Deng and D. Yu, "Deep learning: Methods and applications," *Foundations and Trends in Signal Processing*, vol. 7, no. 3–4. Now Publishers Inc, pp. 197–387, 2013, doi: 10.1561/2000000039.

[4] M. V. Valueva, N. N. Nagornov, P. A. Lyakhov, G. V. Valuev, and N. I. Chervyakov, "Application of the residue number system to reduce hardware costs of the convolutional neural network implementation," *Math. Comput. Simul.*, vol. 177, pp. 232–243, Nov. 2020, doi: 10.1016/j.matcom.2020.04.031.

[5] A. Van Den Oord, S. Dieleman, and B. Schrauwen, "Deep content-based music recommendation," 2013.

[6] R. Collobert and J. Weston, "A unified architecture for natural language processing," in *Proceedings of the 25th international conference on Machine learning - ICML '08*, 2008, pp. 160–167, doi: 10.1145/1390156.1390177.

[7] H. M. Balaha, H. A. Ali, and M. Badawy, "Automatic recognition of handwritten Arabic characters: a comprehensive review," *Neural Computing and Applications*. Springer, pp. 1–24, 17-Jul-2020, doi: 10.1007/s00521-020-05137-6.

[8] A. T. Sahlol, M. Elhoseny, E. Elhariri, and A. E. Hassanien, "Arabic handwritten characters recognition system, towards improving its accuracy," in *Proceedings of the 2017 IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing, INCOS 2017*, 2018, vol. 2018-February, pp. 1–7, doi: 10.1109/ITCOSP.2017.8303068.

[9] H. M. Balaha, H. A. Ali, M. Saraya, and M. Badawy, "A new Arabic handwritten character recognition deep learning system (AHCR-DLS)," *Neural Comput. Appl.*, pp. 1–43, Oct. 2020, doi: 10.1007/s00521-020-05397-2.

[10] N. Altwaijry and I. Al-Turaiki, "Arabic handwriting recognition system using convolutional neural network," *Neural Comput. Appl.*, vol. 8, 2020, doi: 10.1007/s00521-020-05070-8.

[11] G. Latif, J. Alghazo, L. Alzubaidi, M. M. Naseer, and Y. Alghazo, "Deep Convolutional Neural Network for Recognition of Unified Multi-Language Handwritten Numerals," in *2nd IEEE International Workshop on Arabic and Derived Script Analysis and Recognition, ASAR 2018*, 2018, pp. 90–95, doi: 10.1109/ASAR.2018.8480289.

[12] K. Younis, "ARABIC HANDWRITTEN CHARACTER RECOGNITION BASED ON DEEP CONVOLUTIONAL NEURAL NETWORKS," 2018.

[13] M. Torki, M. E. Hussein, A. Elsallamy, M. Fayyaz, and S. Yaser, "Window-Based Descriptors for Arabic Handwritten Alphabet Recognition: A Comparative Study on a Novel Dataset," Nov. 2014.

[14] M. A. Mudhsh and R. Almodfer, "Arabic Handwritten Alphanumeric Character Recognition Using Very Deep Neural Network," *Information*, vol. 8, no. 3, p. 105, Aug. 2017, doi: 10.3390/info8030105.

[15] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings*, 2015.

[16] "HACDB: Handwritten Arabic characters database for automatic character recognition | IEEE Conference Publication | IEEE Xplore." [Online]. Available: https://ieeexplore.ieee.org/abstract/document/6623974. [Accessed: 08-Apr-2021].

[17] "AHDBase." [Online]. Available: http://datacenter.aucegypt.edu/shazeem/. [Accessed: 08-Apr-2021].

[18] A. El-sawy, M. Loey, and H. El-Bakry, "Arabic Handwritten Characters Recognition using Convolutional Neural Network Arabic Handwritten Characters Recognition using Convolutional Neural Network," *WSEAS Trans. Comput. Res.*, vol. 5, pp. 11--19, 2017.

[19] M. M. Rahman, M. A. H. Akhand, S. Islam, C. Shill, and M. M. H. Rahman, "Bangla Handwritten Character Recognition using Convolutional Neural Network," *Image, Graph. Signal Process.*, vol. 8, pp. 52–59, 2015, doi: 10.5815/ijigsp.2015.08.06.

[20] B. Alizadehashraf and S. Roohi, "Persian handwritten character recognition using convolutional neural network," in *Iranian Conference on Machine Vision and Image Processing, MVIP*, 2018, vol. 2017-November, pp. 247–251, doi: 10.1109/IranianMVIP.2017.8342359.

[21] M. Husnain *et al.*, "Recognition of Urdu Handwritten Characters Using Convolutional Neural Network," *Appl. Sci.*, vol. 9, no. 13, p. 2758, Jul. 2019, doi: 10.3390/app9132758.

[22] M. Khalafallah Elbashir and M. E. Mustafa, "Convolutional Neural Network Model for Arabic Handwritten Characters Recognition," *Int. J. Adv. Res. Comput. Commun. Eng.*, vol. 7, no. 11, 2018, doi: 10.17148/IJARCCE.2018.71101.

[23] M. Elleuch, R. Maalej, and M. Kherallah, "A New design based-SVM of the CNN classifier architecture with dropout for offline Arabic handwritten recognition," in *Procedia Computer Science*, 2016, vol. 80, pp. 1712–1723, doi: 10.1016/j.procs.2016.05.512.

[24] M. Pechwitz, S. Snoussi Maddouri, V. Märgner, N. Ellouze, and H.

Amiri, "IFN/ENIT-DATABASE OF HANDWRITTEN ARABIC WORDS."

[25] S. Khan, A. Hafeez, H. Ali, S. Nazir, and A. Hussain, "Pioneer dataset and recognition of Handwritten Pashto characters using Convolution Neural Networks," *Meas. Control*, p. 002029402096482, Nov. 2020, doi: 10.1177/0020294020964826.

[26] M. Elleuch, N. Tagougui, and M. Kherallah, "Arabic handwritten characters recognition using Deep Belief Neural Networks," in *12th International Multi-Conference on Systems, Signals and Devices, SSD 2015*, 2015, doi: 10.1109/SSD.2015.7348121.

[27] A. Ashiquzzaman and A. K. Tushar, "Handwritten Arabic numeral recognition using deep learning neural networks," in *2017 IEEE International Conference on Imaging, Vision and Pattern Recognition, icIVPR 2017*, 2017, doi: 10.1109/ICIVPR.2017.7890866.

[28] "Google Code Archive - Long-term storage for Google Code Project Hosting." [Online]. Available: https://code.google.com/archive/p/cmaterdb/downloads. [Accessed: 08-Apr-2021].

[29] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," *J. Big Data*, vol. 6, no. 1, pp. 1–48, Dec. 2019, doi: 10.1186/s40537-019-0197-0.

[30] S. Joseph and J. George, "Data Augmentation for Handwritten Character Recognition of MODI Script Using Deep Learning Method," in *Smart Innovation, Systems and Technologies*, 2021, vol. 196, pp. 515–522, doi: 10.1007/978-981-15-7062-9_51.

[31] C. Boufenar, A. Kerboua, and M. Batouche, "Investigation on deep learning for off-line handwritten Arabic character recognition," *Cogn. Syst. Res.*, vol. 50, pp. 180–195, Aug. 2018, doi: 10.1016/j.cogsys.2017.11.002.